Domain Adaptation Using Joint Models

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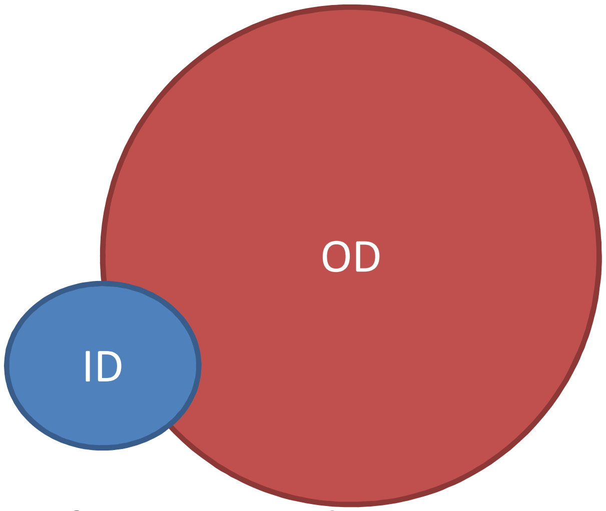
Team




Domain Adaptation



- Preserve lexical choice, writing style, reordering of In-domain genre
- Making best use of the additional general/out-domain data to improve the performance of the system on in-domain task
- Model Weighting
- Data Selection

Model Weighting

- Skew the probability distribution towards ID
  - Concatenate ID data multiple times
  - Weighted interpolation, instance weighting
  - Domain indicator features

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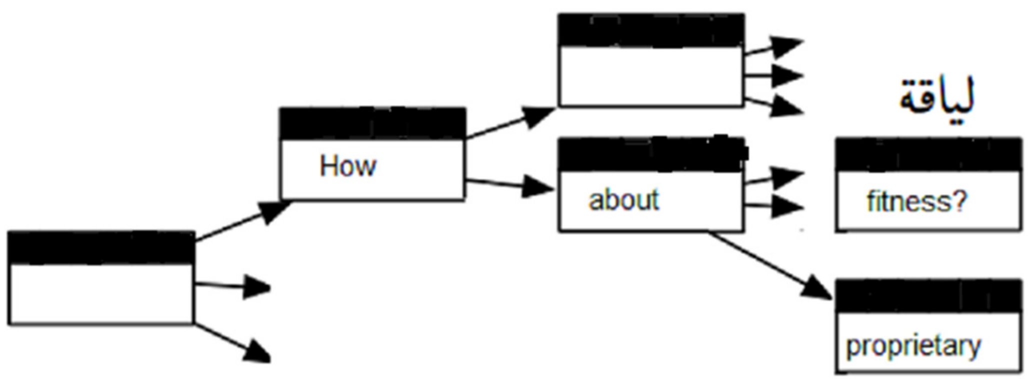
ماذا عن لياقة البدن؟



Data Selection

- Select pseudo-domain data from the out-domain data
  - Train system on In-domain + Concatenation
- Train in and out-domain models
  - Select data based on cross-entropy difference
- Pros
  - Important for speed and memory (SAC Demo)
- Cons
  - Cumbersome to find optimal threshold
  - System cannot fallback to general domain

NNJM Model

- Neural Network Joint Model – NNJM (Devlin et. al 2014: ACL Best Paper)

- Augments language model with source context window

$$P(T|S) \approx \Pi_{i=1}^{|T|} P(t_i | t_{i-1}, \cdots, t_{i-n+1}, \mathcal{S}_i)$$

عن مشكلة الحمل الزائد للاختيار

About the problem of choice overload

- p(problem | the, About, <s> عن, مشكلة, الحمل)
  - Typically 14-gram model (9 source words + 5 target) is used

Why NNJM?

- Handles source and target contextual dependencies across phrasal boundaries
- The n-gram units capture reordering patterns
- Capture semantic dependencies and generalized information
- Gave an improvement of +3.0 BLEU points on top of top ranked Arabic-English NIST system
- Already implemented in Moses and part of SOTA pipeline

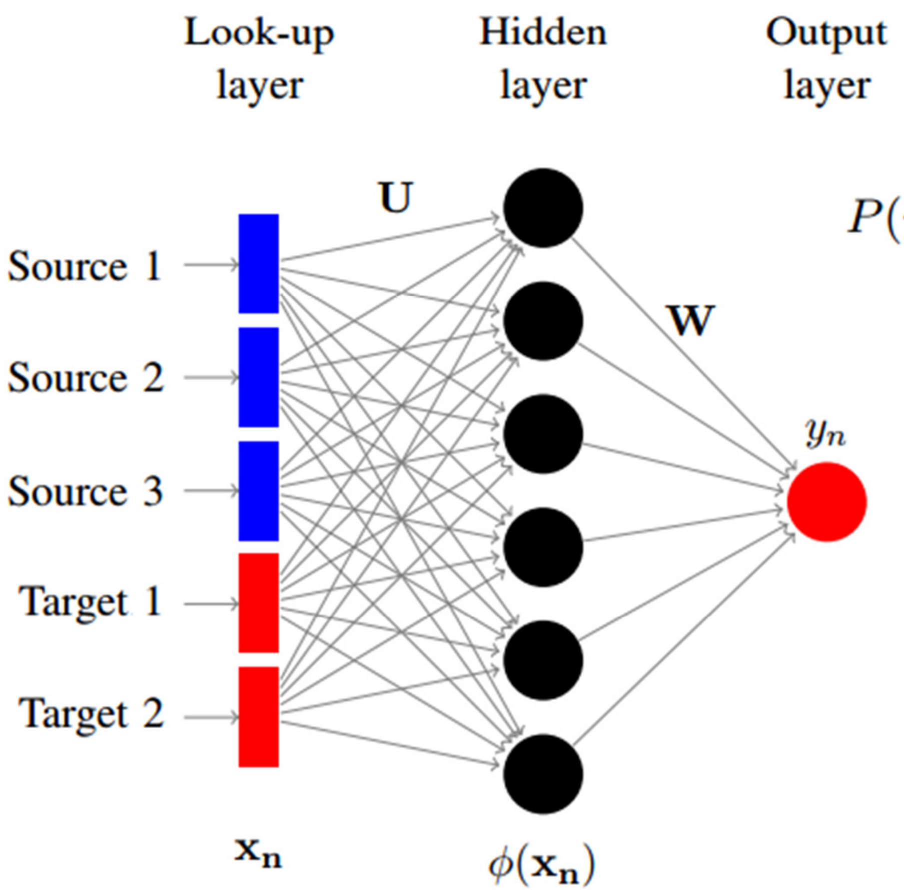
Motivation

- Hypothesis: An NNJM trained on plain concatenation of in- and out-domain data is suboptimal

- Can we learn model in a way that it prefers in-domain?
  - NDAM: Instance weighting by regularizing the loss function
  - NFM: Fusion of in- and out-domain models

- Can we do data selection using NNJM?

NNJM Model



$$P(y_n = k|\mathbf{x_n}, \theta) = \frac{exp\left(\mathbf{w}_k^T \phi(\mathbf{x_n})\right)}{\sum_{m=1}^{|V_o|} exp\left(\mathbf{w}_m^T \phi(\mathbf{x_n})\right)}$$

$$J(\theta) = \sum_{n=1}^{N} \sum_{k=1}^{|V_o|} y_{nk}\, log\, P(y_n = k|\mathbf{x_n}, \theta)$$

NDAM Models – EMNLP ‘16

- NNJM Model trained on plain concatenation might be suboptimal

- We train model on weighted concatenation
  - NDAM-v1: Drift towards out-domain model is controlled using regularizer based on in-domain model
  - NDAM-v2: Regularizer is based on cross entropy difference of in- and out-domain model

NDAM Models – EMNLP '16

- NDAM-v1:

$$J(\theta_a) = \sum_{n=1}^{N} \sum_{k=1}^{|V_o|} \Big[\lambda \, y_{nk} \, logP(y_n = k|\mathbf{x_n}, \theta_a) + (1 - \lambda)$$

$$y_{nk} \, P(y_n = k|\mathbf{x_n}, \theta_i) \, logP(y_n = k|\mathbf{x_n}, \theta_a)\Big]$$

- NDAM-v2:

$$J(\theta_a) = \sum_{n=1}^{N} \sum_{k=1}^{|V_o|} \Big[\lambda \, y_{nk} \, logP(y_n = k|\mathbf{x_n}, \theta_a) + (1 - \lambda)$$

$$y_{nk}\Big[P(y_n = k|\mathbf{x_n}, \theta_i) - P(y_n = k|\mathbf{x_n}, \theta_a\Big] \, logP(y_n = k|\mathbf{x_n}, \theta_a)\Big]$$

Technical Issues

- Handling OOVs
  - Probability of sequences containing OOV is high according to the ID model
  - Mark out-domain OOVs by OOV_o
- Vanishing and Exploding Gradients
  - Gradient clipping [+5,-5]
- NCE to avoid repetitive softmax computation
  - For each training instance, sample 100 samples
  - Unigram versus Uniform
  - NCE loss is defined to discriminate from true instance from noisy ones

Fusion Models (COLING' 2016)

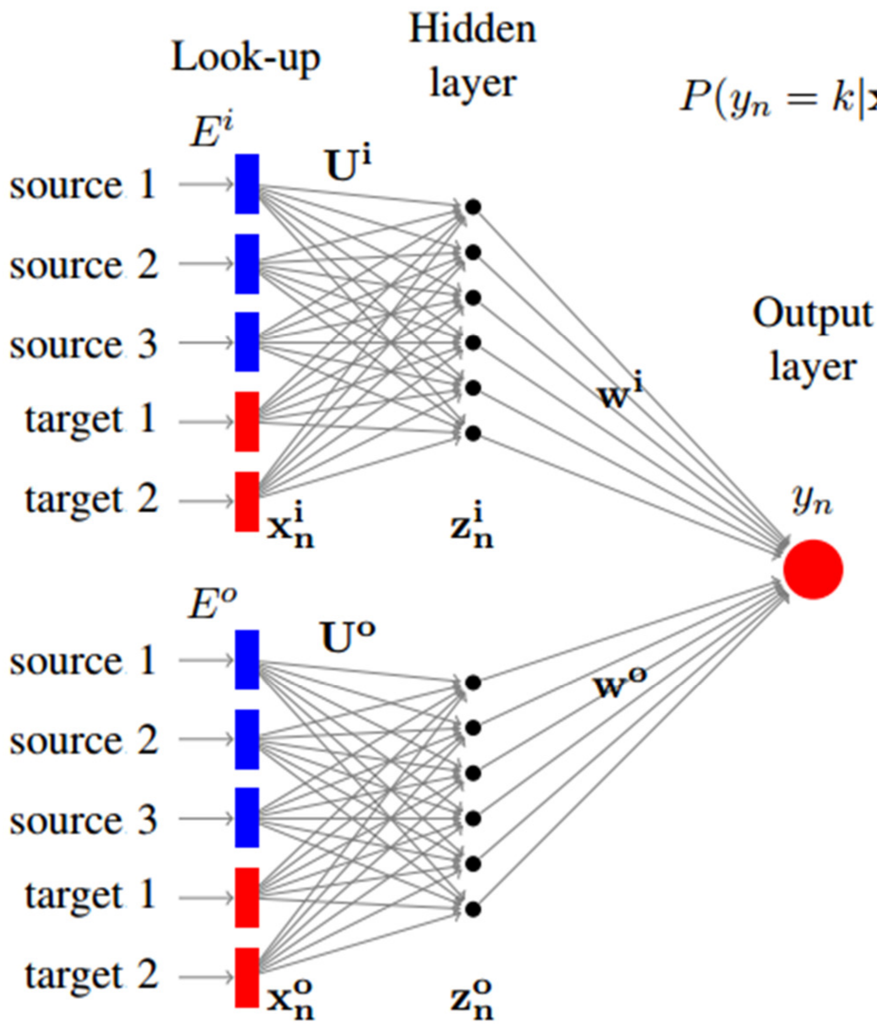
- Motivation: Interpolation of language model, phrase-tables by minimizing perplexity

- Interpolating models to minimize perplexities on tune

$$P(\mathbf{x}_n|\theta,\lambda) = \sum_{d=1}^{D} P(\mathbf{x}_n|z_n = d, \theta_d)\ \lambda_d$$

- NFM: Train in- and out-domain models separately, train a composite model
  - Use in-domain data to back-propagate errors
  - Adjust the weights of embedding and outer layers

Fusion Model



$$P(y_n = k|\mathbf{x_n^i}, \mathbf{x_n^o}, \theta^i, \theta^o) = \frac{\exp\ ([\mathbf{w}_k^i, \mathbf{w}_k^o]^T[\mathbf{z}_n^i, \mathbf{z}_n^o])}{\sum_{m=1}^{|V_o|} \exp\ ([\mathbf{w}_m^i, \mathbf{w}_m^o]^T[\mathbf{z}_n^i, \mathbf{z}_n^o])}$$

$$\nabla_{\mathbf{w}_j^d} J(\theta) = \sum_{n=1}^{N} \Big[(y_{nj} - \sigma_{nj})\mathbf{z}_n^d \Big]$$

Data and Settings

- Language Pairs: Arabic, German
- Data: In-domain: TED, Out-domain: UN (AR), EP, CC, News
- NNJM Settings: Vocab [20K, 40K], word vector size D 150, hidden layer 750, SGD with NCE using 100 noise samples
- Baseline: Moses with SOTA features and settings
- Tune IWSLT dev and test-10-, Test IWSLT[11-13]

Results (Adapting NNJM Models)

	German		Arabic	
System	Avg	Δ	Avg	Δ
Baseline (NNJM)	24.9		28.7	
NDAM	25.3	+0.4	28.9	+0.2
Linear	25.3	+0.4	29.1	+0.4
Log-Linear	25.3	+0.4	29.0	+0.3
Fine Tuning	25.6	+0.7	28.9	+0.2
NFM-I	25.8	+0.9	29.4	+0.7
NFM-II	25.6	+0.7	29.2	+0.5

Results (Phrase-table Adaptation)

	German		Arabic	
System	Avg	Δ	Avg	Δ
Baseline (NNJM)	24.9		28.7	
PT Interpolation	25.2	+ 0.3	28.9	+0.2
Instance Wt.	25.3	+ 0.4	29.2	+0.5
Fill Up	25.1	+ 0.2	28.9	+0.2
NFM-I	25.8	+0.9	29.4	+0.7
NFM-I + Instance Wt.	25.7	+0.8	29.7	+1.0

Results (Data Selection)

	German	Arabic
System	Avg	Avg
Baseline$_{cat}$	24.9	28.7
Baseline$_{ID}$	24.3	29.1
MML	24.7	29.7
+NFM-I	25.2	30.0

Summary

- Novel Domain Adaptation Models based on the NNJM model
  - NDAM models: regularizing loss function based on cross-entropy difference
  - Fusion Models: combining in- and out-domain model through back-propogation
- Applied known techniques
  - Linear interpolation
  - Log-linear interpolation
  - Data Selection using NNJM

Summary

- Fusion models performed best among the methods also beating phrase-table adaption

- We found methods to be complementary
  - Gains on top of phrase-table adaptation and data selection

References

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